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NEURAL DYNAMIC LOGIC OF CONSCIOUSNESS: THE KNOWLEDGE INSTINCT

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14. ABSTRACT:
This report discusses the evolution of consciousness driven by the knowledge instinct, a fundamental mechanism of the mind which determines its higher cognitive functions and neural dynamics. We discuss mathematical difficulties encountered in the past attempts at modeling the mind and relate them to logic. Neural modeling fields and dynamic logic mathematically describe these mechanisms and relate their neural dynamics to the knowledge instinct. Dynamic logic overcomes past mathematical difficulties encountered in modeling intelligence. Mathematical mechanisms of concepts, emotions, instincts, consciousness and unconscious are described and related to perception and cognition. The two main aspects of the knowledge instinct are differentiation and synthesis. Differentiation is driven by dynamic logic and proceeds from vague and unconscious states to more crisp and conscious states, from less knowledge to more knowledge at each hierarchical level of the mind. Synthesis is driven by a hierarchical organization of the mind; it strives to achieve unity and meaning of knowledge: every concept finds its deeper and more general meaning at a higher level. These mechanisms are in complex relationship of symbiosis and opposition, and lead to complex dynamics of evolution of consciousness and cultures. Mathematical modeling of this dynamics in a population leads to predictions for the evolution of consciousness, and cultures. Cultural predictive models can be compared to experimental data and used for improvement of human conditions. We discuss existing evidence and future research directions.

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1. The Knowledge Instinct

To satisfy any instinctual need—for food, survival, and procreation—first and foremost we need to understand what's going on around us. The knowledge instinct is an inborn mechanism in our minds, an instinctual drive for cognition which compels us to constantly improve our knowledge of the world.

Humans and higher animals engage in exploratory behavior, even when basic bodily needs, like eating, are satisfied. Biologists and psychologists have discussed various aspects of this behavior. Harry Harlow discovered that monkeys as well as humans have the drive for positive stimulation, regardless of the satisfaction of drives such as hunger [[i]]; David Berlyne emphasized curiosity as a desire for acquiring new knowledge [[ii]]; Leon Festinger discussed the notion of cognitive dissonance and human drive to reduce the dissonance [[iii]]. Until recently, however, this drive for exploratory behavior was not mentioned among 'basic instincts' on a par with instincts for food and procreation.

The fundamental nature of this mechanism became clear during mathematical modeling of workings of the mind. Our knowledge always has to be modified to fit the current situations. We don't usually see exactly the same objects as in the past: angles, illumination, and surrounding contexts are usually different. Therefore, our internal representations that store past experiences have to be modified; adaptation-learning is required. For example, visual perception (in a simplified way) works as follows [[iv],[v],[vi]]. Images of the surroundings are projected from the retina onto the visual cortex, while at the same time memories-representations of expected objects are projected on the same area of cortex. Perception occurs when actual and expected images coincide. This process of matching representations to sensory data requires modifications-improvement of representations.

In fact virtually all learning and adaptive algorithms (tens of thousands of publications) maximize correspondence between the algorithm internal structure (knowledge in a wide sense) and objects of recognition. Paul Werbos' chapter in this book discusses a fundamental role of reinforcement learning; the knowledge instinct is a reinforcement learning, when reinforcers include correspondence of internal mind representations to the surrounding world. Internal mind representations, or models, which our mind uses for understanding the world, are in constant need of adaptation. Knowledge is not just a static state; it is in a constant process of adaptation and learning. Without adaptation of internal models we would not be able to understand the world. We would not be able to orient ourselves or satisfy any of the bodily needs. Therefore, we have an inborn need, a drive, an instinct to improve our knowledge, and we call it *the knowledge instinct*. It is a foundation of our higher cognitive abilities, and it defines the evolution of consciousness and cultures.

2. Aristotle and Logic

Before we turn to mathematical description of the knowledge instinct, it is instructive to analyze previous attempts at mathematical modeling of the mind. Founders of artificial intelligence in the 1950s and 60s believed that mathematical logic was the fundamental mechanism of the mind, and that using rules of logic they would soon develop computers with

intelligence far exceeding the human mind. Although this belief turned out to be wrong, still many people believe in logic. It plays a fundamental role in many algorithms and even neural networks, and we start from logic to analyze difficulties of mathematical modeling of the mind.

Logic was invented by Aristotle. Whereas multiple opinions may exist on any topic, Aristotle found general rules of reason that are universally valid, and he called this set of rules "logic". He was proud of this invention and emphasized, "Nothing in this area existed before us" (Aristotle, IV BCE, a). However, Aristotle did not think that the mind works logically; he invented logic as a supreme way of argument, not as a theory of the mind. This is clear from many Aristotelian writings, for example from "Rhetoric for Alexander" (Aristotle, IV BCE, b), which he wrote when his pupil, Alexander the Great, requested from him a manual on public speaking. In this book he lists dozens of topics on which Alexander had to speak publicly. For each topic, Aristotle identified two opposing positions (e.g. making peace or declaring war; using or not using torture for extracting the truth, etc.). Aristotle gives logical arguments to support each of the opposing positions. Clearly, Aristotle saw logic as a tool to argue for decisions that were already made; he did not consider logic as the fundamental mechanism of the mind. Logic is, so to speak, a tool for politicians. Scientists follow logic when writing papers and presenting talks, but not to discover new truths about nature.

To explain the mind, Aristotle developed a theory of Forms, which will be discussed later. During the centuries following Aristotle the subtleties of his thoughts were not always understood. With the advent of science, intelligence was often identified with logic. In the 19th century mathematicians striving for exact proofs of mathematical statements noted that Aristotelian ideas about logic were not adequate for this. The foundation of logic, since Aristotle (Aristotle, IV BCE), was the law of excluded middle (or excluded third): every statement is either true or false, any middle alternative is excluded. But Aristotle also emphasized that logical statements should not be formulated too precisely (say, a measure of wheat should not be defined with an accuracy of a single grain). He emphasized that language implies the adequate accuracy, and everyone has his mind to decide what is reasonable. George Boole thought that Aristotle was wrong, that the contradiction between exactness of the law of excluded third and vagueness of language should be corrected.

In this way formal logic, a new branch of mathematics was born. Prominent mathematicians contributed to the development of formal logic, including Gottlob Frege, Georg Cantor, Bertrand Russell, David Hilbert, and Kurt Gödel. Logicians discarded uncertainty of language and founded formal mathematical logic on the law of excluded middle. Many of them were sure that they were looking for exact mechanisms of the mind. Hilbert wrote, "The fundamental idea of my proof theory is none other than to describe the activity of our understanding, to make a protocol of the rules according to which our thinking actually proceeds." (See Hilbert, 1928). In the 1900 he formulated Entscheidungsproblem: to define a set of logical rules sufficient to prove all past and future mathematical theorems. This would formalize scientific creativity and define a logical mechanism for the entire human thinking.

Almost as soon as Hilbert formulated his formalization program, the first hole appeared. In 1902 Russell exposed an inconsistency of formal logic by introducing a set R as follows: *R is a set of all sets which are not members of themselves.* Is R a member of R? If it is not, then it should belong to R according to the definition, but if R is a member of R, this contradicts the definition. Thus either way leads to a contradiction. This became known as the Russell's paradox. Its jovial formulation is as follows: A barber shaves everybody who does not shave himself. Does the barber shave himself? Either answers to this question (yes or no) lead to a

contradiction. This barber, like Russell's set, can be logically defined but cannot exist. For the next 25 years mathematicians where trying to develop a self-consistent mathematical logic, free from paradoxes of this type. But in 1931, Gödel (see in Gödel, 1986) proved that it is not possible, and that formal logic is inexorably inconsistent and self-contradictory.

For a long time people believed that intelligence is equivalent to conceptual logical reasoning. Although it is obvious that the mind is not always logical, since the first successes of science many people came to identify the power of intelligence with logic. This belief in logic has deep psychological roots related to the functioning of the mind. Most of the mind processes are not consciously perceived. For example, we are not aware of individual neuronal firings. We become conscious about the final states resulting from perception and cognition processes; these are perceived by our minds as 'concepts' approximately obeying formal logic. For this reason many people believe in logic. Even after Gödelian theory, founders of artificial intelligence still insisted that logic is sufficient to explain how the mind works.

Let us return to Aristotle. He addressed relationships between logic and the working of the mind as follows. We understand the world due to Forms (representations, models) in our mind. Cognition is a learning process in which a Form-as-potentiality (initial model) meets matter (sensory signals) and becomes a Form-as-actuality (a concept). Whereas Forms-actualities are logical, Forms-potentialities do not obey logic. Here Aristotle captured an important aspect of the working of the mind which has eluded many contemporary scientists. Logic is not a fundamental mechanism of the mind, but rather the result of mind's illogical operations. Later we describe the mathematics of dynamic logic, which gives a mathematical explanation for this process: how logic appears from illogical states and processes. It turns out that dynamic logic is equivalent to the knowledge instinct.

3. Mechanisms of the Mind

The basic mind mechanisms making up operations of the knowledge instinct are described mathematically in the next section. Here we give a conceptual preview of this description. Among the mind's cognitive mechanisms, the most directly accessible to consciousness are concepts. Concepts are like internal models of the objects and situations in the world. This analogy is quite literal, e.g., as already mentioned, during visual perception of an object, a concept-model in our memory projects an image onto the visual cortex, which is matched there to an image, projected from retina. This simplified description will be refined later.

Concepts serve to satisfy the basic instincts, which have emerged as survival mechanisms long before concepts. Current debates regarding instincts, reflexes, motivational forces, and drives, often lump together various mechanisms. This is inappropriate for the development of mathematical description of the mind mechanisms. I follow proposals (see Grossberg & Levine, 1987; Perlovsky 2006, for further references and discussions) to separate instincts as internal sensor mechanisms indicating the basic needs, from "instinctual behavior," which should be described by appropriate mechanisms. Accordingly, I use the word "instincts" to describe mechanisms of internal sensors: for example, when a sugar level in blood goes below a certain level an instinct "tells us" to eat. Such separation of instinct as "internal sensor" from "instinctual behavior" is only a step toward identifying all the details of relevant biological mechanisms.

How do we know about instinctual needs? Instincts are connected to cognition and behavior by emotions. Whereas in colloquial usage, emotions are often understood as facial

expressions, higher voice pitch, exaggerated gesticulation, these are outward signs of emotions, serving for communication. A more fundamental role of emotions within the mind system is that emotional signals evaluate concepts for the purpose of instinct satisfaction. This evaluation does not take place according to rules or concepts (like in rule-systems of artificial intelligence), but according to a different instinctual-emotional mechanism, described first by Grossberg and Levine (1987); the role of emotions in the working of the mind is considered in this book in chapter by Daniel Levine. Below we describe emotional mechanisms for higher cognitive functions.

Emotions evaluating satisfaction or dissatisfaction of the knowledge instinct are not directly related to bodily needs. Therefore, they are 'spiritual' emotions. We perceive them as harmony-disharmony between our knowledge and the world (between our understanding of how things ought to be and how they actually are in the surrounding world). According to Immanuel Kant [[vii]] these are aesthetic emotions (emotions that are not related directly to satisfaction or dissatisfaction of bodily needs).

Aesthetic emotions related to learning are directly noticeable in children. The instinct for knowledge makes little kids, cubs, and piglets jump around and play fight. Their inborn models of behavior must adapt to their body weights, objects, and animals around them long before the instincts of hunger and fear will use the models for the direct aims of survival. In adult life, when our perception and understanding of the surrounding world is adequate, aesthetic emotions are barely perceptible: the mind just does its job. Similarly, we do not usually notice adequate performance of our breathing muscles and satisfaction of the breathing instinct. However, if breathing is difficult, negative emotions immediately reach consciousness. The same is true about the knowledge instinct and aesthetic emotions: if we do not understand the surroundings, if objects around do not correspond to our expectations, negative emotions immediately reach consciousness. We perceive these emotions as disharmony between our knowledge and the world. Thriller movies exploit the instinct for knowledge: their personages are shown in situations in which knowledge of the world is inadequate for survival.

Let me emphasize again, aesthetic emotions are not peculiar to art and artists, they are inseparable from every act of perception and cognition. In everyday life we usually do not notice them. Aesthetic emotions become noticeable at higher cognitive levels in the mind hierarchy, when cognition is not automatic, but requires conscious effort. Antonio Damasio's view [[viii]] of emotions defined by visceral mechanisms, as far as discussing higher cognitive functions, seems erroneous in taking secondary effects for the primary mechanisms.

In the next section we describe a mathematical theory of conceptual-emotional recognition and understanding, which is the essence of neural cognitive dynamics. As we discuss, in addition to concepts and emotions, this theory involves the mechanisms of intuition, imagination, conscious, and unconscious. This process is intimately connected to an ability of the mind to think, to operate with symbols and signs. The mind involves a heterarchy of multiple levels. It is not a strict hierarchy, but a heterarchy, because it involves feedback connections throughout many levels; to simplify discussion we often refer to the mind stricture as a hierarchy. Hierarchy of multiple levels of cognitive mechanisms: knowledge instinct, concept-models, and emotions, operate at each level from simple perceptual elements (like edges, or moving dots), to concept-models of objects, to relationships among objects, to complex scenes, and up the hierarchy… toward the concept-models of the meaning of life and purpose of our existence. Hence the tremendous complexity of the mind, yet relatively few basic principles of the mind organization explain neural evolution of this system.

4. Neural Modeling Fields

Neural Modeling Fields (NMF) is a neural architecture that mathematically implements the mechanisms of the mind discussed above. It is a multi-level, hetero-hierarchical system [ix]. The mind is not a strict hierarchy; there are multiple feedback connections among adjacent levels, hence the term hetero-hierarchy. At each level in NMF there are concept-models encapsulating the mind's knowledge; they generate so-called top-down neural signals, interacting with input, bottom-up signals. These interactions are governed by the knowledge instinct, which drives concept-model learning, adaptation, and formation of new concept-models for better correspondence to the input signals.

This section describes a basic mechanism of interaction between two adjacent hierarchical levels of bottom-up and top-down signals (fields of neural activation). Sometimes it will be more convenient to talk about these two signal-levels as an input to, and output from, a (single) processing-level. At each level, output signals are concepts recognized in (or formed from) input signals. Input signals are associated with (or recognized, or grouped into) concepts according to the models and the knowledge instinct at this level. This general structure of NMF corresponds to our knowledge of neural structures in the brain; still, in this chapter we do not map mathematical mechanisms in all their details to specific neurons or synaptic connections.

At a particular hierarchical level, we enumerate neurons by the index n = 1,... N. These neurons receive bottom-up input signals, $\mathbf{X}(n)$, from lower levels in the processing hierarchy. $\mathbf{X}(n)$ is a field of bottom-up neuronal synapse activations, coming from neurons at a lower level. Each neuron has a number of synapses. For generality, we describe each neuron activation as a set of numbers, $\mathbf{X}(n) = \{X_d(n), d = 1,... D\}$. Top-down, or priming signals, to these neurons are sent by concept-models, $\mathbf{M}_h(\mathbf{S}_h,n)$, and we enumerate models by the index h = 1,... H. Each model is characterized by its parameters, $\mathbf{S}_h$; in the neuron structure of the brain they are encoded by strength of synaptic connections. Mathematically, we describe them as a set of numbers, $\mathbf{S}_h = \{S^a_h, a = 1,... A\}$. Models *represent* signals in the following way. Say, signal $\mathbf{X}(n)$ is coming from sensory neurons activated by object *h*, characterized by a model $\mathbf{M}_h(\mathbf{S}_h,n)$ and parameter values $\mathbf{S}_h$. These parameters may include position, orientation, or lighting of an object *h*. Model $\mathbf{M}_h(\mathbf{S}_h,n)$ predicts a value $\mathbf{X}(n)$ of a signal at neuron *n*. For example, during visual perception, a neuron *n* in the visual cortex receives a signal $\mathbf{X}(n)$ from retina and a priming signal $\mathbf{M}_h(\mathbf{S}_h,n)$ from an object-concept-model *h*. A neuron *n* is activated if both bottom-up signal from lower-level-input and top-down priming signal are strong. Various models compete for evidence in the bottom-up signals, while adapting their parameters for better match as described below. This is a simplified description of perception. The most benign everyday visual perception uses many levels from retina to object perception. The NMF premise is that the same laws describe the basic interaction dynamics at each level. Perception of minute features, or everyday objects, or cognition of complex abstract concepts is due to the same mechanism described in this section. Perception and cognition involve models and learning. In perception, models correspond to objects; in cognition, models correspond to relationships and situations.

The knowledge instinct drives learning, which is an essential part of perception and cognition. Learning increases a similarity measure between the sets of models and signals, $L(\{\mathbf{X}\},\{\mathbf{M}\})$. The similarity measure is a function of model parameters and associations between

the input bottom-up signals and top-down, concept-model signals. For concreteness I refer here to an object perception using a simplified terminology, as if perception of objects in retinal signals occurs in a single level.

In constructing a mathematical description of the similarity measure, it is important to acknowledge two principles (which are almost obvious) [x]. First, the visual field content is unknown before perception occurred and second, it may contain any of a number of objects. Important information could be contained in any bottom-up signal; therefore, the similarity measure is constructed so that it accounts for all bottom-up signals, **X**(n),

$$L(\{\mathbf{X}\},\{\mathbf{M}\}) = \prod_{n \in N} l(\mathbf{X}(n)). \tag{1}$$

This expression contains a product of partial similarities, l(**X**(n)), over all bottom-up signals; therefore it forces the mind to account for every signal (even if one term in the product is zero, the product is zero, the similarity is low and the knowledge instinct is not satisfied); this is a reflection of the first principle. Second, before perception occurs, the mind does not know which object gave rise to a signal from a particular retinal neuron. Therefore a partial similarity measure is constructed so that it treats each model as an alternative (a sum over models) for each input neuron signal. Its constituent elements are conditional partial similarities between signal **X**(n) and model $\mathbf{M}_h$, l(**X**(n)|h). This measure is "conditional" on object h being present, therefore, when combining these quantities into the overall similarity measure, L, they are multiplied by r(h), which represent a probabilistic measure of object h actually being present. Combining these elements with the two principles noted above, a similarity measure is constructed as follows:

$$L(\{\mathbf{X}\},\{\mathbf{M}\}) = \prod_{n \in N} \sum_{h \in H} r(h)\, l(\mathbf{X}(n) \mid h). \tag{2}$$

The structure of (2) follows standard principles of the probability theory: a summation is taken over alternatives, *h*, and various pieces of evidence, *n*, are multiplied. This expression is not necessarily a probability, but it has a probabilistic structure. If learning is successful, it approximates probabilistic description and leads to near-optimal Bayesian decisions. The name "conditional partial similarity" for l(**X**(n)|h) (or simply l(n|h)) follows the probabilistic terminology. If learning is successful, l(n|h) becomes a conditional probability density function, a probabilistic measure that signal in neuron *n* originated from object *h*. Then L is a total likelihood of observing signals {**X**(n)} coming from objects described by models $\{\mathbf{M}_h\}$. Coefficients r(h), called priors in probability theory, contain preliminary biases or expectations, expected objects *h* have relatively high r(h) values; their true values are usually unknown and should be learned, like other parameters $\mathbf{S}_h$.

We note that in probability theory, a product of probabilities usually assumes that evidence is independent. Expression (2) contains a product over *n*, but it does not assume independence among various signals **X**(n). Partial similarities l(n|h) are structured in a such a way (described later) that they depend on differences between signals and models; these differences are due to measurement errors and can be considered independent. There is a dependence among signals due to models: each model $\mathbf{M}_h(\mathbf{S}_h,n)$ predicts expected signal values in many neurons *n*.

During the learning process, concept-models are constantly modified. Here we consider a case when functional forms of models, $\mathbf{M}_h(\mathbf{S}_h,n)$, are all fixed and learning-adaptation involves only model parameters, $\mathbf{S}_h$. More complicated structural learning of models is considered in [xi, xii]. From time to time a system forms a new concept, while retaining an old one as well; alternatively, old concepts are sometimes merged or eliminated. This requires a modification of the similarity measure (2); the reason is that more models always result in a better fit between the models and data. This is a well known problem, it is addressed by reducing similarity (2) using a "skeptic penalty function," p(N,M) that grows with the number of models M, and this growth is steeper for a smaller amount of data N. For example, an asymptotically unbiased maximum likelihood estimation leads to multiplicative $p(N,M) = \exp(-N_{par}/2)$, where N_{par} is a total number of adaptive parameters in all models (this penalty function is known as Akaike Information Criterion, see [ix] for further discussion and references).

The knowledge instinct demands maximization of the similarity (2) by estimating model parameters **S** and associating signals with concepts. Note that all possible combinations of signals and models are accounted for in expression (2). This can be seen by expanding a sum in (2), and multiplying all the terms; it would result in H^N items, a very large number. This is the number of combinations between all signals (N) and all models (H).

This very large number of combinations was a source of difficulties (that we call combinatorial complexity, CC) for developing intelligent algorithms and systems since the 1950s. The problem was first identified in pattern recognition and classification research in the 1960s and was named "the curse of dimensionality" [xiii]. It seemed that adaptive self-learning algorithms and neural networks could learn solutions to any problem 'on their own' if provided with a sufficient number of training examples. It turned out that training examples should encompass not only all individual objects that should be recognized, but also objects in the context, that is combinations of objects. Self-learning approaches encountered CC of learning requirements.

Rule-based systems were proposed in the 1960s to solve the problem of learning complexity. An initial idea was that rules would capture the required knowledge and eliminate a need for learning [xiv]. However, in presence of variability the number of rules grew; rules depended on other rules, combinations of rules had to be considered and rule systems encountered CC of rules. Beginning in the 1980s, model-based systems were proposed. They used models that depended on adaptive parameters. The idea was to combine advantages of learning-adaptivity and rules by using adaptive models. The knowledge was encapsulated in models, whereas unknown aspects of particular situations was to be learned by fitting model parameters (see [xv] and discussions in [ix,xvi]). Fitting models to data required selecting data subsets corresponding to various models. The number of subsets, however, is combinatorially large (N^M as discussed above). A general popular algorithm for fitting models to data, multiple hypotheses testing [xvii], is known to face CC of computations. Model-based approaches encountered computational CC (N and NP complete algorithms).

It turns out that CC is related to the most fundamental mathematical result of the 20th c., Gödel's theory of inconsistency of logic [xviii, xix]. Formal logic is based on the "law of excluded middle," according to which every statement is either true or false and nothing in between. Therefore, algorithms based on formal logic have to evaluate every variation in data or models as a separate logical statement (hypothesis). CC of algorithms based on logic is a manifestation of the inconsistency of logic in finite systems. Multivalued logic and fuzzy logic were proposed to overcome limitations related to the law of excluded third [xx]. Yet the mathematics of

multivalued logic is no different in principle from formal logic, “excluded third” is substituted by “excluded n+1.” Fuzzy logic encountered a difficulty related to the degree of fuzziness. Complex systems require different degrees of fuzziness in various subsystems, varying with the system operations; searching for the appropriate degrees of fuzziness among combinations of elements again would lead to CC. Is logic still possible after Gödel? A recent review of the contemporary state of this field shows that logic after Gödel is much more complicated and much less logical than was assumed by the founders of artificial intelligence. The problem of CC remains unresolved within logic [[xxi]].

Various manifestations of CC are all related to formal logic and Gödel theory. Rule systems relied on formal logic in a most direct way. Self-learning algorithms and neural networks relied on logic in their training or learning procedures, every training example was treated as a separate logical statement. Fuzzy logic systems relied on logic for setting degrees of fuzziness. CC of mathematical approaches to theories of the mind is related to the fundamental inconsistency of logic.

5. Dynamic Logic

5.1 Mathematical formulation

NMF solves the CC problem by using dynamic logic [[xxii,xxiii,xxiv,x]]. An important aspect of dynamic logic is matching vagueness or fuzziness of similarity measures to the uncertainty of models. Initially, parameter values are not known, and uncertainty of models is high; so is the fuzziness of the similarity measures. In the process of learning, models become more accurate, and the similarity measure more crisp, the value of the similarity increases. This is the mechanism of dynamic logic.

Mathematically it is described as follows. First, assign any values to unknown parameters, $\{\mathbf{S}_h\}$. Then, compute association variables f(h|n),

$$f(h|n) = r(h)\, l(\mathbf{X}(n)|h) \,/ \sum_{h' \in H} r(h')\, l(\mathbf{X}(n)|h'). \qquad (3)$$

Eq.(3) looks like the Bayes’ formula for a posteriori probabilities; if l(n|h) in the result of learning become conditional likelihoods, f(h|n) become Bayesian probabilities for signal *n* originating from object *h*. The dynamic logic of NMF is defined as follows,

$$df(h|n)/dt = f(h|n) \sum_{h' \in H} \{[\delta_{hh'} - f(h'|n)] \cdot$$
$$[\partial \ln l\,(n|h')/\partial \mathbf{M}_{h'}]\, \partial \mathbf{M}_{h'}/\partial \mathbf{S}_{h'} \cdot d\mathbf{S}_{h'}/dt, \qquad (4)$$

$$d\mathbf{S}_h/dt = \sum_{n \in N} f(h|n)[\partial \ln l(n|h)/\partial \mathbf{M}_h]\partial \mathbf{M}_h/\partial \mathbf{S}_h, \qquad (5)$$

here

$\delta_{hh'}$ is 1 if h=h', 0 otherwise. (6)

Parameter t is the time of the internal dynamics of the MF system (like a number of internal iterations). These equations define the neural dynamics of NMF.

Gaussian-shape functions can often be used for conditional partial similarities,

$$l(n|h) = G(\mathbf{X}(n) \mid \mathbf{M}_h(\mathbf{S}_h, n), \mathbf{C}_h). \qquad (7)$$

Here G is a Gaussian function with mean $\mathbf{M}_h$ and covariance matrix $\mathbf{C}_h$. Note, a "Gaussian assumption" is often used in statistics; it assumes that signal distribution is Gaussian. This is not the case in (7): here signal is not assumed to be Gaussian. Eq. (7) is valid if *deviations* between the model **M** and signal **X** are Gaussian; these deviations usually are due to many random causes and are therefore Gaussian. If they are not Gaussian, appropriate functions could be used. If there is no information about the functional shapes of conditional partial similarities, still (7) is a good choice, it is not a limiting assumption: a weighted sum of Gaussians in (2) can approximate any positive function, like similarity.

Covariance matrices, $\mathbf{C}_h$, in (7) are estimated like other unknown parameters, as shown in eq.(5). Initially they are set to large values, corresponding to uncertainty in the knowledge of models, $\mathbf{M}_h$. As parameter values and models improve, covariances are reduced to intrinsic differences between models and signals (due to sensor errors, or model inaccuracies). As covariances get smaller, similarities get crisper, closer to delta-functions; association variables (3) get closer to crisp {0, 1} values, and dynamic logic solutions converge to crisp logic. This process of concurrent parameter improvement and convergence of similarity to a crisp logical function is an essential part of dynamic logic. This is the mechanism of dynamic logic defining the neural dynamics of NMF.

The dynamic evolution of fuzziness from large to small is the reason for the name "dynamic logic." Mathematically, this mechanism helps avoiding local maxima during convergence [ix,xxvxxxii], and psychologically it explains many properties of the mind, as discussed later. Whichever functional shapes are used for conditional partial similarities, they ought to allow for this process of matched convergence in parameter values and similarity crispness. The brain might use various mechanisms for realizing the dynamic logic process at various stages. The chapter in this book by Emilio Del-Moral-Hernandez considers neural networks with recursive processing elements (RPE), which might implement dynamic logic through their chaotic dynamics. In RPE neural networks high vagueness of dynamic logic states and the knowledge instinct dissatisfaction corresponds to high value of the parameter *p* and to chaotic wide searches. Low vagueness, successful perception and cognition, and the knowledge instinct satisfaction corresponds to low *p* and ordered dynamics. Similar correspondence between dynamic logic, the knowledge instinct, and chaotic dynamic might be applicable to discussions in Walter Freeman chapter in this book. Dynamic logic seems to correspond to transitions from highly chaotic to lower chaotic states in cortical neural activity.

The following theorem was proved [ix].

Theorem. Equations (3) through (6) define a convergent dynamic NMF system with stationary states defined by $\max_{\{\mathbf{S}_h\}} L$.

It follows that the stationary states of a NMF system are the maximum similarity states satisfying the knowledge instinct. When partial similarities are specified as probability density functions (pdf), or likelihoods, the stationary values of parameters $\{\mathbf{S}_h\}$ are asymptotically

unbiased and efficient estimates of these parameters [xxvi]. A computational complexity of dynamic logic is linear in N.

In plain English, this means that dynamic logic is a convergent process. It converges to the maximum of similarity, and therefore satisfies the knowledge instinct. Several aspects of NMF convergence are discussed in later sections. If likelihood is used as similarity, parameter values are estimated efficiently (that is, in most cases, parameters cannot be better learned using any other procedure). Moreover, as a part of the above theorem, it is proven that the similarity measure increases at each iteration. The psychological interpretation is that the knowledge instinct is satisfied at each step: a NMF system with dynamic logic *enjoys* learning.

Let us emphasize again, the fundamental property of dynamic logic is evolution from vague, uncertain, fuzzy, unconscious states to more crisp, certain, conscious states.

5.2 Example of operation

Operations of NMF are illustrated in Fig. 1 using an example of detection and tracking of moving objects in clutter [xxvii]. Tracking is a classical problem, which becomes combinatorially complex in clutter when target signals are below the clutter level. Solving this problem is usually approached by using multiple hypotheses tracking algorithm [xxviii], which evaluates multiple hypotheses about which signals came from which of the moving objects, and which from clutter. This standard approach is well-known to face CC [ix], because large numbers of combinations of signals and models have to be considered. Fig. 1 illustrates NMF neurodynamics while solving this problem.

Fig. 1(a) shows true track positions, while Fig. 1(b) shows the actual data available for detection and tracking. It contains 6 sensor scans on top of each other (time axis is not shown). The data set consists of 3000 data points, 18 of which belong to three moving objects. In this data, the target returns are buried in clutter, with signals being weaker than clutter (by factor of 2). Figs. 1(c)-1(h) illustrate evolution of the NMF models as they adapt to the data during iterations. Fig. 1(c) shows the initial vague-fuzzy model, while Fig. 1(h) shows the model upon convergence at 20 iterations. Between (c) and (h) the NMF neural network automatically decides how many model components are needed to fit the data, and simultaneously adapts the model parameters, including target track coefficients. There are two *types* of models: one uniform model describing clutter (it is not shown), and linear track models with large uncertainty. In (c) and (d), the NMF neural network fits the data with one model, and uncertainty is somewhat reduced. Between (d) and (e) NMF decides that it needs two models to 'understand' the content of the data. Fitting with 2 tracks continues until (f); between (f) and (g) a third track is added. Iterations stop at (h), when similarity stops increasing. Detected tracks closely correspond to the truth (a). In this case NMF successfully detected and tracked all three objects and required only 10^6 operations, whereas a straightforward application of multiple hypotheses tracking would require $H^N \sim 10^{1500}$ operations. This number, larger than the size of the Universe and too large for computation, prevents past algorithms from solving this problem. NMF overcoming this difficulty achieved about 100 times improvement in terms of signal-to-clutter ratio. This improvement is achieved by using dynamic evolution from vague and uncertain models to crisp and certain (instead of sorting through combinations).

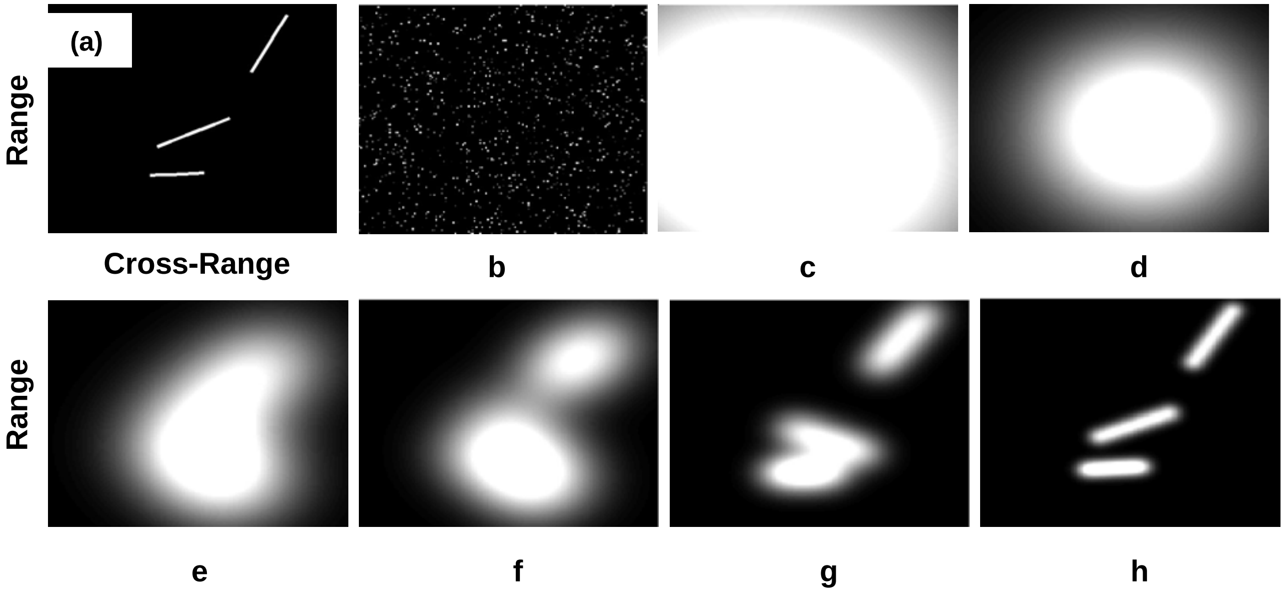

Figure 1. Detection and tracking objects below clutter using NMF: (a) true track positions; (b) actual data available for detection and tracking. Evolution of the NMF neural network driven by the knowledge instinct is shown in (c) – (h), where (c) shows the initial, uncertain, model and (h) shows the model upon convergence after 20 iterations. Converged model (h) are in close agreement with the truth (a). Performance improvement of about 100 in terms of signal-to-clutter ratio is achieved due to dynamic logic evolution from vague and uncertain models to crisp and certain.

6. Conscious, Unconscious, and Differentiation

NMF dynamics described above satisfy the knowledge instinct and improve knowledge by evolving vague, uncertain models toward crisp models, which maximize similarity between models and data. This process of knowledge accumulation, driven by the instinct for knowledge, proceeds in the minds of every member in a society and constitutes an essential aspect of cultural evolution. Vague and uncertain models are less accessible to consciousness, whereas crisp and concrete models are more conscious.

Most of the mind's operations are not accessible to consciousness. We definitely know that neural firings and connections cannot be perceived consciously. In the foundations of the mind there are material processes in the brain inaccessible to consciousness. Jung suggested that conscious concepts are developed by the mind based on genetically inherited structures, archetypes, which are inaccessible to consciousness [[xxix],[xxx]]. Grossberg [[iv]] suggested that only signals and models attaining a resonant state (that is signals matching models) can reach consciousness. It was further detailed by Taylor [[xxxi]]; he related consciousness to the mind being a control mechanism of the mind and body. A part of this mechanism is a prediction model. When this model predictions differ from sensory observations, this difference may reach a resonant state, which we are conscious about. To summarize the above analyses, the mind mechanisms, described in NMF by dynamic logic and fuzzy models, are not accessible to

consciousness. Final results of dynamic logic processes, resonant states characterized by crisp models and corresponding signals are accessible to consciousness. Increase in knowledge and improved cognition results in better, more diverse, more differentiated consciousness.

How did the evolution of cognition and consciousness proceed? What was the initial state of consciousness: an undifferentiated unity or a "booming, buzzing confusion" [xxxii]? Or, let us take a step back in evolutionary development and ask, what is the initial state of pre-conscious psyche? Or, let us move back even further toward the evolution of sensory systems and perception. Why would an evolution result in sensor organs? Obviously, such an expensive thing as a sensor is needed to achieve specific goals: to sense the environment with the purpose to accomplish specific tasks. Evolution of organisms with sensors went together with an ability to utilize sensory data.

In the process of evolution, sensory abilities emerged together with perception abilities. A natural evolution of sensory abilities could not result in a "booming, buzzing confusion," but must result in evolutionary advantageous abilities to avoid danger, attain food, etc. Primitive perception abilities (observed in primitive animals) are limited to a few types of concept-objects (light-dark, warm-cold, edible-nonedible, dangerous-attractive...) and are directly 'wired' to proper actions (Walter Freeman and Robert Kozma chapters in this book refer to this primitive intelligence as low dimensional chaos; high dimensional chaos appears with higher intelligence). When perception functions evolve further, beyond immediate actions, it is through the development of complex internal model-concepts, which unify simpler object-models into a unified and flexible model of the world. Only at this point of possessing relatively complicated differentiated concept-models composed of a large number of sub-models, can an intelligent system experience a "booming, buzzing confusion" if it faces a new type of environment. A primitive system is simply incapable of perceiving confusion: It perceives only those 'things' for which it has concept-models. If its perceptions do not correspond to reality, it does not experience confusion, but simply ceases to survive. When a baby is born, it undergoes a tremendous change of environment, most likely without much conscious confusion. The original state of consciousness is undifferentiated unity. It possesses a single modality of primordial undifferentiated Self-World.

The initial unity of psyche limited the abilities of the mind, and further development proceeded through the differentiation of psychic functions or modalities (concepts, emotions, behavior); they were further differentiated into multiple concept-models, etc. This accelerated adaptation. Differentiation of consciousness began millions of years ago. It accelerated tremendously in our recent past, and still continues today [xxxiii, xxix, xxxiv].

In pre-scientific literature about mechanisms of the mind there was a popular idea of homunculus, that is, a little mind inside our mind which perceived our perceptions and made them available to our mind. This naive view is amazingly close to the actual scientific explanation. The fundamental difference is that the scientific explanation does not need an infinite chain of homunculi inside homunculi. Instead, there is a hierarchy of the mind models with their conscious and unconscious aspects. The conscious differentiated aspect of the models decreases at higher levels in the hierarchy, and they are more uncertain and fuzzy. At the top of the hierarchy there are most general and important models of the meaning of our existence (which we discuss later); these models are mostly unconscious.

Our internal perceptions of consciousness are due to Ego-model. This model essentially consists of, or has access to other model parts that are available to consciousness. It is the mind

mechanism of what used to be called ‘homunculus.’ It ‘perceives’ crisp conscious parts of other models, in the same way that models of perception ‘perceive’ objects in the world. The properties of consciousness as we experience them, such as continuity and identity of consciousness, are due to properties of the Ego-model, [x]. These properties of unity, continuity, and identity, are the reasons to assume existence of this model. What is known about this ‘consciousness’-model? Since Freud, a certain complex of psychological functions was called Ego. Jung considered Ego to be based on a more general model or archetype of Self. Jungian archetypes are psychic structures (models) of a primordial origin, which are mostly inaccessible to consciousness, but determine the structure of our psyche. In this way, archetypes are similar to other models, e.g., receptive fields of the retina are not consciously perceived, but determine the structure of visual perception. The Self archetype determines our phenomenological subjective perception of ourselves, and in addition, structures our psyche in many different ways, which are far from being completely understood. An important phenomenological property of Self is the perception of uniqueness and in-divisibility (hence, the word individual).

According to Jung, conscious concepts of the mind are learned on the basis of inborn unconscious psychic structures, archetypes, [xxix]. Contemporary science often equates the mechanism of concepts with internal representations of objects, their relationships, situations, etc. The origin of internal representations-concepts is from two sources, inborn archetypes and culturally created models transmitted by language [xii].

In preceding sections we described dynamic logic operating at a single hierarchical level of the mind. It evolves vague and unconscious models-concepts into more crisp and conscious. Psychologically this process was called by Carl Jung *differentiation* of psychic content [xxix].

7. Hierarchy and Synthesis

In previous sections we described a single processing level in a hierarchical NMF system. As we mentioned, the mind is organized in an approximate hierarchy. For example, in visual cortex, this approximate hierarchy is well studied [iv,v]. Not every two models are in hierarchical relationships (above-below or same level, more or less general, etc.). Also, feedback loops between higher and lower levels contradict to strict hierarchical ordering. Nevertheless, for simplicity, we will talk about the mind as a hierarchy (in terms of generality of models and the directions of bottom-up and top-down signal flows). At each level of the hierarchy there are input signals from lower levels, models, similarity measures (2), emotions (which are changes in similarity), and actions. Actions include adaptation, i.e., behavior satisfying the knowledge instinct. This adaptation corresponds to the maximization of similarity, as described mathematically by equations (3) through (6). An input to each level is a set of signals X(n), or in neural terminology, an input field of neuronal activations. The result of dynamic logic operations at a given level are activated models, or concepts h recognized in the input signals n; these models along with the corresponding instinctual signals and emotions may activate behavioral models and generate behavior at this level.

The activated models initiate other actions. They serve as input signals to the next processing level, where more general concept-models are recognized or created. Output signals from a given level, serving as input to the next level, could be model activation signals, a_h, defined as

$$a_h = \sum_{n \in N} f(h|n). \quad (8)$$

As defined previously in (3) f(h|n) can be interpreted as a probability that signal n came from object h; and a_h is interpreted as a total activation of the concept h from all signals. Output signals may also include model parameters. The hierarchical NMF system is illustrated in Fig. 2. Within the hierarchy of the mind, each concept-model finds its mental meaning and purpose at a higher level (in addition to other purposes). For example, consider a concept-model "chair." It has a "behavioral" purpose of initiating sitting behavior (if sitting is required by the body), this is the "bodily" purpose at the same hierarchical level. In addition, "chair" has a "purely mental" purpose at a higher level in the hierarchy, a purpose of helping to recognize a more general concept, say of a "concert hall," which model contains rows of chairs.

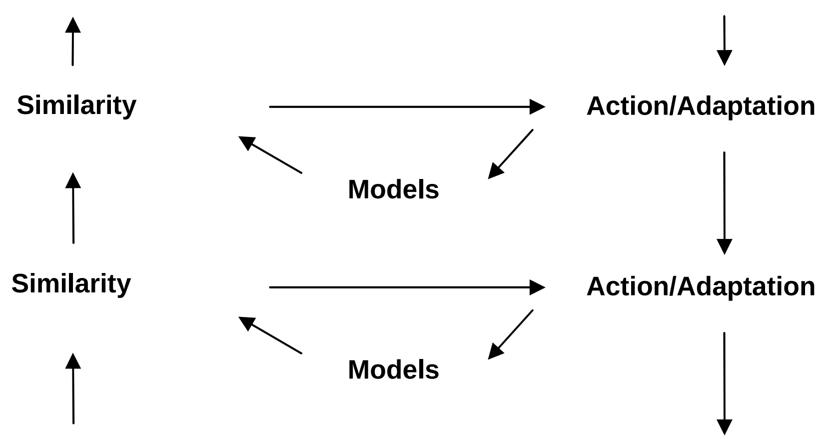

Figure 2. Hierarchical NMF system. At each level of a hierarchy there are models, similarity measures, and actions (including adaptation, maximizing the knowledge instinct - similarity). High levels of partial similarity measures correspond to concepts recognized at a given level. Concept activations are output signals at this level and they become input signals to the next level, propagating knowledge up the hierarchy. Each concept-model finds its mental meaning and purpose at a higher level.

Models at higher levels in the hierarchy are more general than models at lower levels. For example, if we consider the vision system, models at the very bottom of the hierarchy correspond (roughly speaking) to retinal ganglion cells and perform similar functions; they detect simple features in the visual field. At higher levels, models correspond to functions performed at V1 and higher up in the visual cortex, that is detection of more complex features such as contrast edges, their directions, elementary moves, etc. Visual hierarchical structures and models have been studied in detail [iv,v], and these models can be used in NMF. At still higher cognitive levels, models correspond to objects, to relationships among objects, to situations, and relationships among situations, etc. [x]. At still higher levels, even more general models reside,

corresponding to complex cultural notions and relationships such as family, love, friendship, and abstract concepts such as law, rationality, etc. The contents of these models correspond to the wealth of cultural knowledge, including the writings of Shakespeare and Tolstoy. Mechanisms of the development of these models are reviewed in the next section. According to Kantian analysis [[xxxv]], at the top of the hierarchy of the mind are models of the meaning and purpose of our existence, unifying our knowledge, and the corresponding behavioral models aimed at achieving this meaning. Chapter by Robert Kozma in this book considers a related neural architecture, K-sets, describing a hierarchy of the mind.

From time to time, as discussed, a system forms a new concept or eliminates an old one. Many pattern recognition algorithms and artificial neural networks lack this important ability of the mind. It can be modeled mathematically in several ways; adaptive resonance theory (ART) uses vigilance threshold [[xxxvi]], which is similar to a threshold for a similarity measure [[ix]]. A somewhat different mechanism of NMF works as follows. At every level, the system always keeps a reserve of vague (fuzzy) inactive concept-models (with large covariance, C, eq.7). They are inactive in that their parameters are not adapted to the data; therefore their similarities to signals are low. Yet, because of a large fuzziness (covariance) the similarities are not exactly zero. When a new signal does not fit well into any of the active models, its similarities to inactive models automatically increase (because first, every piece of data is accounted for and second, inactive models are vague-fuzzy and potentially can "grab" every signal that does not fit into more specific, less fuzzy, active models). When the activation signal a_h of eq.(8) for an inactive model, h, exceeds a certain threshold, the model is activated. Similarly, when an activation signal for a particular model falls below a threshold, the model is deactivated. Thresholds for activation and deactivation are set usually based on information existing at a higher hierarchical level (prior information, system resources, numbers of activated models of various types, etc.). Activation signals for active models at a particular level $\{ a_h \}$ form a "neuronal field," which serve as input signals to the next level, where more abstract and more general concepts are formed, and so on along the hierarchy toward higher models of meaning and purpose.

Models at a higher level act as "eyes" perceiving the models at a lower level. Each higher level in the hierarchy is the "mind of a homunculus" perceiving the meaning of what was recognized at a lower level. As mentioned, this does not lead to an infinite regress, because higher level models are more general, more uncertain, and more vague and fuzzy.

Let us note that in the hierarchical structure (Fig. 2) concept-models at the bottom level of the hierarchy correspond to objects directly perceived in the world. Perception mechanisms to a significant extent are determined by sensor organs which evolved over billions of years. Models at this level are to a large extent the result of evolution and to a lesser extent the result of cultural constructions. These models are "grounded" in "real" objects existing in the surrounding world. For example, "food" objects are perceived not only by the human mind, but also by all pre-human animals.

This is not true for concept-models at higher levels of the hierarchy. These more abstract and more general models are cultural constructs (to some extent). They cannot be perceived directly in the surrounding world (e.g., concept-models of "rationality," or "meaning and purpose of life"). These concepts cannot just emerge in the mind on their own as some useful combination of simpler concepts. Because there are a huge number of combinations of simpler concepts, an individual human being does not have enough time in his or her life to accumulate enough experiential evidence to verify the usefulness of these combinations. These higher level concepts accumulate in cultures due to languages. An individual mind is assured about the

usefulness of certain high-level concept-models because he can talk about them with other members of the society (with a degree of mutual understanding). Concepts acquired from language are not automatically related to events or combinations of objects in the surrounding world. For example, every five-year-old knows about "good guys" and "bad guys." Yet, still at 40 or 70 nobody could claim the he or she can perfectly use these models to understand the surrounding world. Philosophers and theologians have argued about the meaning of good and evil for thousands of years, and these arguments are likely to continue forever. The study of mechanisms relating language concepts to concept-models of cognition have just begun [[x], [xii], [xxxiv], [xxxvii], [xxxviii]].

The hierarchical structure of the mind is not a separate mechanism, independent from the knowledge instinct. Detailed neural and mathematical mechanisms connecting these two are still a matter of ongoing and future research [[x], [xii], [xxxiv], [xxxvii]]. Here we outline some basic principles of the knowledge instinct operation in the mind hierarchy. Previous sections described the mechanism of differentiation, creating diverse and detailed models, acting at a single level of hierarchy. At a single level, the meaning of each model is to satisfy the knowledge instinct by finding patterns in the input data, bottom-up signals, and adapting to these patterns. There are also meanings and purposes related to bodily instincts: for example, food objects can be used to satisfy needs for food and desires for eating. In this chapter we limit our discussion to spiritual needs, to the knowledge instinct.

We have discussed that models acquired deeper meanings and purposes at higher hierarchical levels. The knowledge instinct acting at higher levels and aesthetic emotions at higher levels are perceived more consciously then at lower levels. The pure aesthetic feeling of harmony between our knowledge and the surrounding world at lower levels is below threshold of conscious registration in our minds. We do not feel much joy from the understanding of simple objects around us. But we do enjoy solving complex problems that required a lot of time and effort. This emotional feel of harmony from improving-creating high level concept-models is related to the fact that high level concepts unify many lower level concepts and increase the overall meaning and purpose of our diverse knowledge. Jung called this synthesis, which he emphasized is essential for psychological well being.

Synthesis, the feel of overall meaning and purpose of knowledge, is related to the meaning and purpose of life, which we perceive at the highest levels of the hierarchy of the mind. At those high levels models are intrinsically vague and undifferentiated, not only in terms of their conceptual content, but also in terms of differentiation of conceptual and emotional. At the highest levels of the mind the two are not quite separable. This inseparability, which we sometimes feel as a meaning and purpose of our existence, is important for evolution and survival. If the hierarchy of knowledge does not support this feel, the entire hierarchy would crumble, which was an important (or possibly the most important) mechanism of destruction of old civilizations. The knowledge instinct demands satisfaction at the lowest levels of understanding concrete objects around, and also at the highest levels of the mind hierarchy, understanding of the entire knowledge in its unity, which we feel as meaning and purpose of our existence. This is the other side of the knowledge instinct, a mechanism of *synthesis* [[xxix]].

8. Evolutionary Dynamics of Consciousness and Cultures

8.1 Neurodynamics of differentiation and synthesis

Every individual mind has limited experience over the lifetime. Therefore, a finite number of concept-models are sufficient to satisfy the knowledge instinct. It is well appreciated in many engineering applications, that estimating a large number of models from limited data is difficult and unreliable; many different solutions are possible, one no better than the other. Psychologically, the average emotional investment in each concept decreases with an increase in the number of concepts, and a drive for differentiation and creating more concepts subsides. Emotional investment in a concept is a measure of the meaning and purpose of this concept within the mind system, that is, a measure of synthesis. Thus, the drive for differentiation requires synthesis. More synthesis leads to faster differentiation, whereas more differentiation decreases synthesis.

In a hierarchical mind system, at each level some concepts are used more often than other, they acquire multiple meanings, leading to a process opposite to differentiation. These more general concepts "move" to a higher hierarchical levels. These more general, higher-level concepts are invested with more emotion. This is a process of synthesis increase.

Another aspect of synthesis is related to language. Most concepts within individual minds are acquired with the help of language. Interaction between language and cognition is an active field of study (see [xii] for neurodynamics of this interaction and for more references). Here we do not go into the details of this interaction, we just emphasize the following. First, creation of new concepts by differentiation of inborn archetypes is a slow process, taking millennia; results of this process, new concepts, are stored in language, which transmits them from generation to generation. Second, a newborn mind receives this wealth of highly differentiated concepts "ready-made," that is without real-life experience, without understanding and differentiating cognitive concepts characterizing the world; a child at 5 or 7 can speak about much of existing cultural content, but it would take the rest of life to understand, how to use this knowledge. This is directly related to the third aspect of language-cognition interaction: language model-concepts are not equivalent to cognitive model-concepts. Language models serve to understand language, not the world around. Cognitive models that serve to understand the world are developed in individual minds with the help of language. This development of cognitive models from language models, connection of language and cognition is an important aspect of synthesis.

Let us dwell a bit more on this aspect of synthesis. Learning language is driven by the language instinct [xxxix]; it involves aesthetic emotions; a child likes to learn language. However, this drive and related emotions subside after about 7, after language is mostly learned. During the rest of life, the knowledge instinct drives the mind to create and improve cognitive models on the basis of language models [xii]. This process involves aesthetic emotions related to learning cognitive concepts. Again, synthesis involves emotions.

People are different in their ability to connect language and cognition. Many people are good at talking, without fully understanding how their language concepts are related to real life. On any subject, they can talk one way or another without much emotional investment. Synthesis of language and cognition involves synthesis of emotional and conceptual contents of psyche.

Synthesis of emotional and conceptual is also related to hierarchy. Higher level concepts are more general and vaguer. They are less differentiated not only in their conceptual precision,

but also their conceptual and emotional contents are less differentiated. Important high-level concepts are more emotional than low-level, mundane, everyday concepts. They are also less conscious (remind, more differentiation leads to more conscious content). Therefore, synthesis connects language and cognition, concepts and emotions, conscious and unconscious. This is opposite of differentiation; we all have high-value concepts (related to family life, or to political cause, or to religion) which are so important to us and so emotional, that we cannot “coldly analyze,” cannot differentiate them. “Too high” level of synthesis invests concepts with “too much” emotional-value contents, so that differentiation is stifled.

To summarize, differentiation and synthesis are in complex relationships, at once symbiotic and antagonistic. Synthesis leads to spiritual inspiration, to active creative behavior leading to fast differentiation, to creation of knowledge, to science and technology. At the same time, “too” high level of synthesis stifles differentiation. Synthesis is related to hierarchical structure of knowledge and values. At the same time, high level of differentiation discounts psychological emotional values of individual concepts, and destroys synthesis, which was the basis for differentiation. In sections 3, 4 and 5 we presented a NMF / DL mathematical model of neurodynamics of differentiation. We lack at present same detail level of neurodynamics of synthesis. In this section we make first steps toward developing mathematical evolutionary model of interacting differentiation and synthesis. Both mechanisms act in the minds of individual people. Future detailed models will develop neural mechanisms of synthesis, will account for mechanisms of cognition, emotion, and language, and will study multi-agent systems, in which each agent possesses complex neurodynamics of interaction between differentiation and synthesis. We call such an approach neural micro-dynamics. Lacking these micro-dynamics models, in this section we develop simpler models averaged over population.

8.2 Macro-dynamics

As a first step here we develop simplified evolutionary dynamic models similar to mean field theories in physics. These models describe the neural mechanisms of differentiation, synthesis, and hierarchy using measures averaged over population of interacting agents, abstracting from details of emotional and language mechanisms. A future challenge would be to relate these models to nonlinear dynamic models discussed in this book in chapters by Walter Freeman and Robert Kozma. We call this averaging method “neural macro-dynamics.” We start with simplest dynamic equations inspired by neurodynamics of differentiation and synthesis, discuss their properties, and evaluate needed modification toward developing a “minimal” realistic model. Results of this analysis can be used in sociological cultural studies to understand past, present, and future of cultures, emerging cultural phenomena, and to improve current and future models.

We characterize accumulated knowledge, or differentiation, by a “mean field” averaged quantity, D, which represents the average number of concept-models used in a population. When considered alone, separate from other mechanisms driving neurodynamics, the simplest dynamical equation is

$$dD/dt = a. \tag{9}$$

This equation describes linear growth in the complexity of culture as measured by accumulated knowledge, or differentiation, D. The next step toward more realistic modeling accounts for the

fact that differentiation involves developing new, more detailed models from the old ones. Therefore the speed of differentiation is proportional to accumulated knowledge, i.e.,

$$dD/dt = aD. \tag{10}$$

Here, a is a constant. The solution of this equation describes an exponential growth of knowledge, i.e.,

$$D(t) = D_0 \exp(at). \tag{11}$$

Both of the above equations could be considered "minimally realistic" in the short term. In the long term, however, they are too optimistic, too simple, and not realistic. We know that continuous growth in knowledge may exist in some cultures over limited time periods, however occasionally the growth in knowledge and conceptual diversity is interrupted and culture disintegrates or stagnates. This is true in all known cultures, e.g., Western culture disintegrated and stagnated during the Middle Ages. Whereas some researchers have attributed the disintegration of Roman Empire to barbarians or to lead poisoning [[xl]], here we would like to search for possible intrinsic spiritual, neurodynamic mechanisms.

According to our previous discussions, and following Jung analysis [[xxix]], a more complicated dynamic of knowledge accumulation involves synthesis, S. Synthesis characterizes the relationship between knowledge and its instinctive, emotional, value in the society. For example, a ratio of the similarity measure and differentiation, LL/D, measures a degree of satisfaction of the knowledge instinct (2) per concept-model. A closely related, but more instrumental, measure available for sociological research [[xli]] is an average measure of emotional investment per concept in a society. With the growth of differentiation, the emotional value of every individual concept diminishes, and therefore the simplest neurodynamic equation for synthesis is (below, b is a constant)

$$dS/dt = -bD. \tag{12}$$

According to the previous analysis, synthesis inspires creativity and stimulates differentiation. The simplest modification of eq.(9), accounting for influence of synthesis is

$$dD/dt = aS. \tag{13}$$

These equations are similar to the brain dynamic equations for KII-sets discussed in R. Kozma chapter in this book. Together, eqs. (12) and (13) lead to oscillating solutions with frequency ω and phase ϕ_0, i.e.,

$$\begin{aligned} &D(t) = D_0 \cos(\omega t + \phi_0), \quad \omega = \mathrm{sqrt}(ab) \\ &S(t) = -(D_0\, \omega / a) \sin(\omega t + \phi_0). \end{aligned} \tag{14}$$

These solutions are unsatisfactory, however, because here D and S can assume negative values, whereas differentiation and synthesis cannot become negative by their very definition.

A more realistic equation for differentiation would account for the following. The speed of differentiation is proportional to accumulated knowledge, D, and is enhanced by synthesis, S,

and is therefore proportional to D*S. We have to take into account that, psychologically, synthesis is a measure of the meaning and purpose in knowledge and culture, it is a necessary condition for human existence, and it has to remain positive. When synthesis falls below certain positive value, S_0, knowledge loses any value, culture disintegrates, and differentiation reverses its course, i.e.,

$$dD/dt = a\,D\,(S - S_0). \tag{15}$$

Still, eq. (12) is unsatisfactory since it always leads to decrease in synthesis, so that any cultural revival and long term accumulation of knowledge is impossible. The long-term joint solution of eqs. (15) and (12) is $D \approx 0$, $S \approx S_0$.

From the previous analysis, we know that synthesis is created in hierarchies. Diverse, differentiated, knowledge at particular level in a hierarchy acquires meaning and purpose at the next level. The simplest measure of hierarchy, H, is the number of hierarchical levels, on average, in the minds of the population. A useful measure would have to account for conceptual hierarchy and the hierarchy of values. Accounting for hierarchical synthesis, eq.(12) can be re-written as

$$dS/dt = -bD + dH. \tag{16}$$

Here, d is a constant. If the hierarchy, H, is genetically or culturally fixed to a constant value, eqs. (16) and (15) have several joint solutions. Let us explore them. First, there is a long-term solution with constant knowledge and synthesis:

$$\begin{aligned} D &= (b/d)\,H \\ S &= S_0. \end{aligned} \tag{17}$$

Here, differentiation and synthesis reach constant values and do not change with time. The hierarchy of concepts (and values) is rigidly fixed. This could be a reasonable solution, describing highly conservative, traditional societies in a state of cultural stagnation. The conceptual hierarchy, H, reaches a certain level, then remains unchanged, and this level forever determines the amount of accumulated knowledge or conceptual differentiation. Synthesis is at a low level S_0. All cultural energy is devoted to maintaining this synthesis, and further accumulation of knowledge or differentiation is not possible. Nevertheless, such a society might be stable for a long time. Some Polynesian and New Guinean cultures, lacking writing or complex religion and practicing cannibalism, still maintained stability and survived for millennia [[xlii]]. Chinese culture had stagnated since early BCE until recent times, although at much higher level of the hierarchy. It would be up to cultural historians and social scientists to evaluate whether such cultures are described by the above mathematical solution and, if so, what particular values of model parameters are appropriate.

Alternatively, if evolution starts with $S > S_0$, differentiation first grows exponentially ~ $\exp(\,a\,(S-S_0)\,t\,)$. This eventually leads to the term $-bD$ in (16) overtaking dH, so that synthesis diminishes and the differentiation growth exponent is reduced. When $S < S_0$, differentiation falls until $bD = dH$, at which point differentiation grows again, and the cycle continue. This type solution is illustrated in Fig. 3.

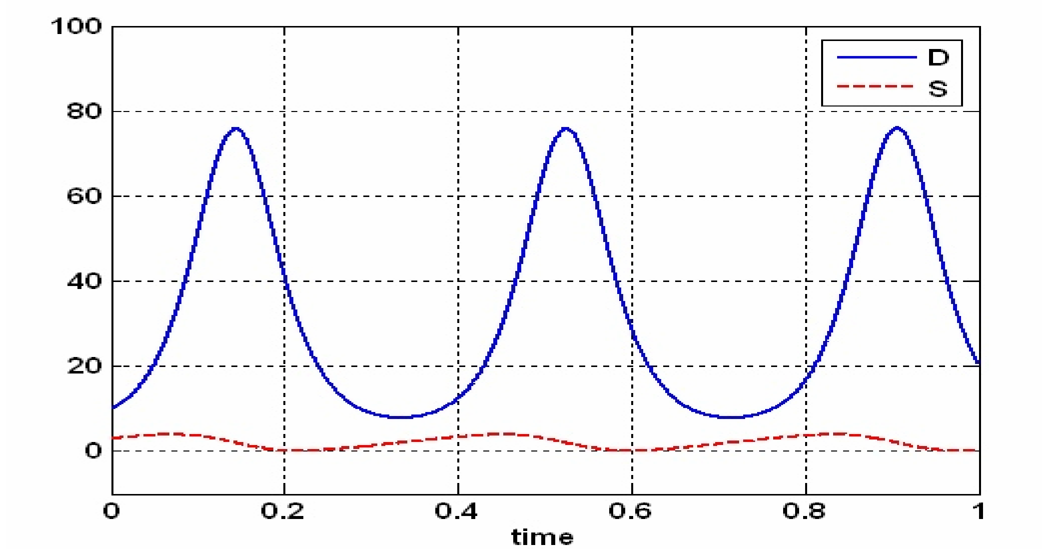

Figure 3. Evolution of differentiation and synthesis described by eqs. (15, 16) with parameter values a = 10, b = 1, d = 10, S_0=2, H_0 = 3, and initial values D(t=0) = 10, S(t=0) = 3.

Here, the solid line indicates the cycles of differentiation. When comparing this line with historical cultural data, one should remember that the time scale here has not been determined. Cycles that peak when cultures flourish and end with devastation and loss of knowledge take centuries. However, we should not disregard much shorter cultural cycles, for example, fascism in Germany or communism in Soviet Union, which have occurred in the 20th century. Fig. 3 indicates the loss of about 85% of knowledge (D) within a cycle; is this reasonable? Before answering this question, we should emphasize that the frequency of oscillations and top-to-bottom amplitude depend upon the values of the parameters used. We had no data with which we could select scientifically correct values for the parameters. It will be up to sociologists and cultural historians to decide upon appropriate parameter values. Another topic for future studies will be the appropriate measure of D. Possibly, the proper measure of D is an average knowledge per person, not over the entire population, but only over the part of population actively involved in running states. In "well managed" societies, educated people are actively involved in society management. In "badly managed" societies, like Soviet Union, educated people were excluded from voicing their opinion, and a few poorly educated people made the decisions. Therefore, 85% loss of knowledge during fast oscillations may represent the loss of knowledge and synthesis in the "ruling class," but not in the entire society.

Notwithstanding these arguments, the wild oscillations in differentiation and synthesis shown in Fig. 3 may not be reasonable. It might be an indication that eqs. (15, 16) are simplified and may be missing some important mechanisms creating synthesis. Roles of mechanisms such as religion, art, music are discussed in the last section; their mathematical modeling is beyond the scope of this chapter.

Oscillating solutions similar to Fig.3 are also possible if evolution starts with $S < S_0$. First, differentiation will fall, but then dH will exceed bD (in eq.16), synthesis will grow and thus the oscillating solutions ensue. These oscillating solutions describe many civilizations over extended periods of time, e.g. Western civilization over millennia. Again, it would be up to

cultural historians and social scientists to evaluate which cultures are described by this solution, and what particular values of model parameters are appropriate.

The dashed line in Fig. 3 indicates the cycles of synthesis. In this example synthesis falls to 0, which is probably not realistic. We could have keep synthesis strictly positive by selecting different values of parameters, but these kinds of detailed studies are not our purpose here. We would like to emphasize that there is presently no scientific data that can be used to select reasonable parameter values for various societies; this is a subject of future research. Similarly, the many cycles exactly repeated in this figure indicate the simplistic nature of this model.

8.3 Expanding hierarchy

Expanding knowledge in the long term requires expanding hierarchical levels. As discussed, differentiation proceeds at each hierarchical level, including the highest levels. In this process, knowledge accumulating at a particular level in the hierarchy may lead to certain concept-models being used more often than others. These concepts used by many agents in a population in slightly different ways acquire more general meanings and give rise to concepts at a higher level. Thus, increasing differentiation may induce more complex hierarchy, and the hierarchy expands, i.e.,

$$dH/dt = e\ dD/dt. \qquad (18)$$

Eqs. (18), (16), and (15) describe a culture expanding in its knowledge content and in its hierarchical complexity. For example, a solution with fixed high level of synthesis can be described by

$$\begin{aligned} &S = \text{const} > S_0, \\ &D(t) = D_0 \exp(\ a(S - S_0)t\ ), \\ &H(t) = H_0 + e_c\ D_0 \exp(\ a(S - S_0)t\ ). \qquad (19) \end{aligned}$$

This solution implies the following “critical” value for parameter e,

$$e_c = b / d\ . \qquad (20)$$

Fig. 4 illustrates this expanding-culture solution with constant synthesis. If $e > e_c$, than synthesis, differentiation, and hierarchy grow indefinitely, as shown in Fig. 5.

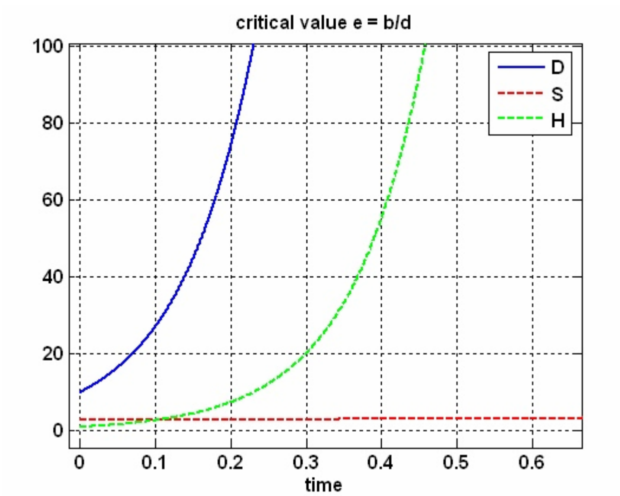

Fig. 4

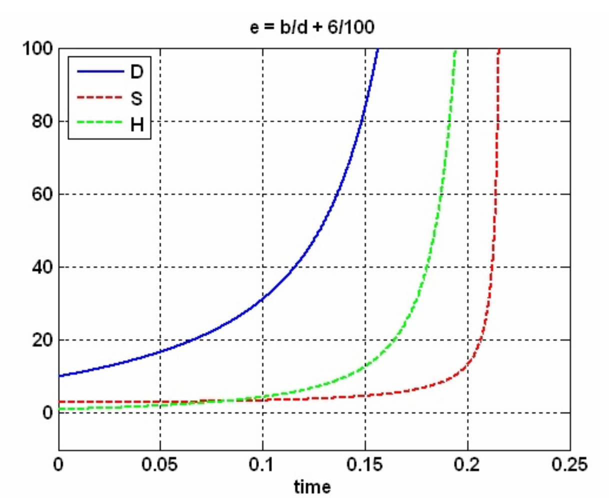

Fig. 5

Figure 4. Exponentially expanding solutions. Evolution of differentiation, synthesis, and hierarchy is described by eqs. (15, 16, 19) with parameter values a = 10, b = 1, d = 10, S_0=2, H_0 = 1, and initial values D(t=0) = 10, S(t=0) = 3. In Fig. 4 e = b/d = 0.1 (eq.20).

Figure 5. Exponentially expanding solutions. Evolution of differentiation, synthesis, and hierarchy is described by eqs. (15, 16, 19) with parameter values a = 10, b = 1, d = 10, S_0=2, H_0 = 1, and initial values D(t=0) = 10, S(t=0) = 3. In Fig. 5 e = 1.06.

These solutions with unbounded growth in knowledge, its hierarchical organization and, in Fig. 5, growing stability (synthesis) are too optimistic compared to the actual evolution of human societies.

If $e < e_c$, then synthesis and knowledge hierarchy collapse when differentiation destructs synthesis. However, when differentiation falls, $H_0 > e_c D_0 \exp(a(S - S_0)t)$, synthesis again starts growing, leading to the growth of differentiation. After a fast flourishing period, synthesis again is destructed by differentiation when its influence on synthesis overtakes that of the hierarchy, and culture collapses. These periods of collapse and growth alternate, as shown in Fig.6.

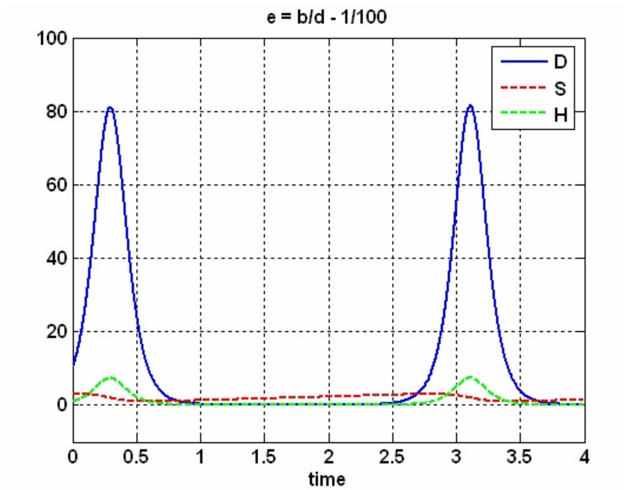

Figure 6. Alternating periods of cultural growth and stagnation, same parameter values as above, except e = 0.99 < b/d.

This assumption of the hierarchy growing in sync with differentiation (18) is too optimistic. The growth of hierarchy involves the differentiation of models at the highest level, which involve concepts of the meaning and purpose of life. These concepts cannot be made fully conscious, and in many societies they involve theological and religious concepts of the Highest. Changes in these concepts involve changes of religion, such as from Catholicism to Reformation, they involve national upheavals and wars, and they do not always proceed smoothly as in (18). Currently we do not have theory adequate to describe these changes; therefore we proceed within a single fixed religious paradigm. This can be approximately described as constant hierarchy H, as in the previous section. Alternatively we can consider slowly expanding hierarchy,

$$H(t) = H_0 + e^*t. \qquad (21)$$

The solution of eqs. (15, 16, 21) is illustrated in Fig. 7.

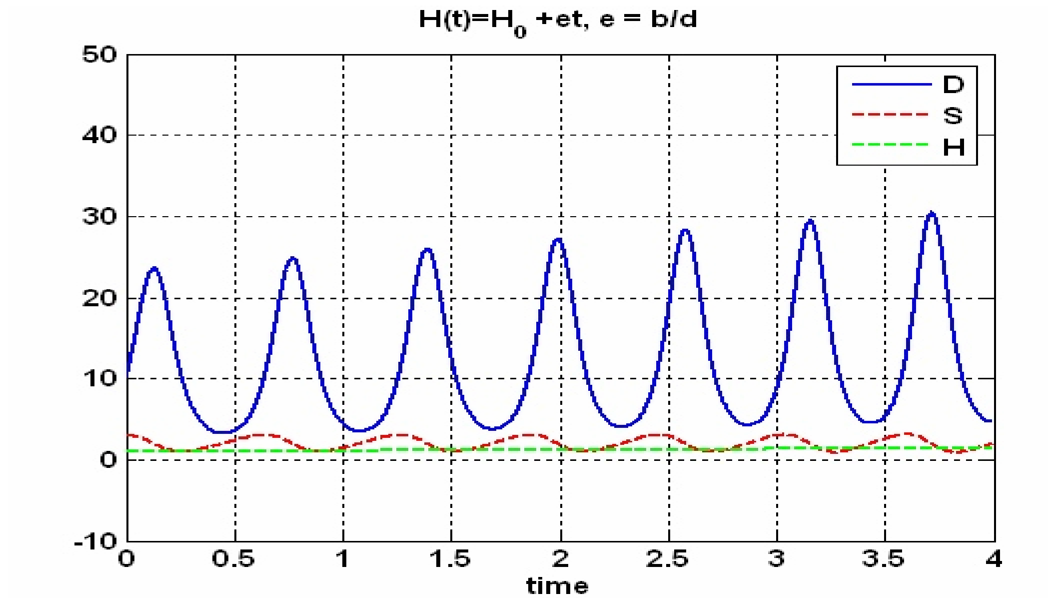

Figure 7. Oscillating and growing differentiation and synthesis (eqs. 15, 16, 21); slow growth corresponds to slowly growing hierarchy, e = 0.1. Note, increase in differentiation leads to somewhat faster oscillations.

This growing and oscillating solution might describe Judeo-Christian culture over the long period of its cultural evolution. Whereas highly ordered structure is a consequence of the simplicity of equations, this solution does not repeat exactly the same pattern, rather the growth of hierarchy leads to growth of differentiation, and to faster oscillations. Note, the evolution and recoveries from periods of stagnation in Western culture were sustained by the growing hierarchy of knowledge and values. This stable, slow growing hierarchy was supported by religion. However, science has been replacing religion in many people's minds (in Europe more so than in the US) approximately since the Enlightenment (the 18th c.). The current cultural neurodynamics in Western culture are characterized by the predominance of scientific differentiation and the lack of synthesis. More and more people have difficulty connecting scientific highly-differentiated concepts to their instinctual needs. Many turn to psychiatrists and take medications to compensate for a lack of synthesis. The stability of Western hierarchical values is precarious, and during the next down-swing of synthesis hierarchy may begin to disintegrate, leading to cultural collapse. Many think that this process is already happening, more so in Europe than in the US.

8.4 Dual role of synthesis

The previous section considered only the inspirational role of synthesis. The effect of synthesis, as discussed previously, is more complex: high investment of emotional value in every concept makes concepts "stable" and difficult to modify or differentiate [[xii]]. Therefore, a high level of synthesis leads to stable and stagnating culture. We account for this by changing the effect of synthesis on differentiation as follows:

$$dD/dt = a\, D\, G(S), \quad G(S) = (S - S_0) \exp(-(S-S_0)/ S_1) \tag{22}$$
$$dS/dt = -b\, D + d\, H \tag{23}$$
$$H(t) = H_0, \text{ or } H(t) = H_0 + e^*t. \tag{24}$$

Solutions similar to those previously considered are possible: a solution with a constant value of synthesis similar to (17), as well as oscillating and oscillating-growing solutions.

A new type solution possible here involves a high level of synthesis with stagnating differentiation. If dH > bD, then according to (23) synthesis grows exponentially, whereas differentiation levels off, and synthesis continues growing. This leads to a more and more stable society with high synthesis, with high emotional values attached to every concept, while knowledge accumulation stops, as shown in Fig. 8.

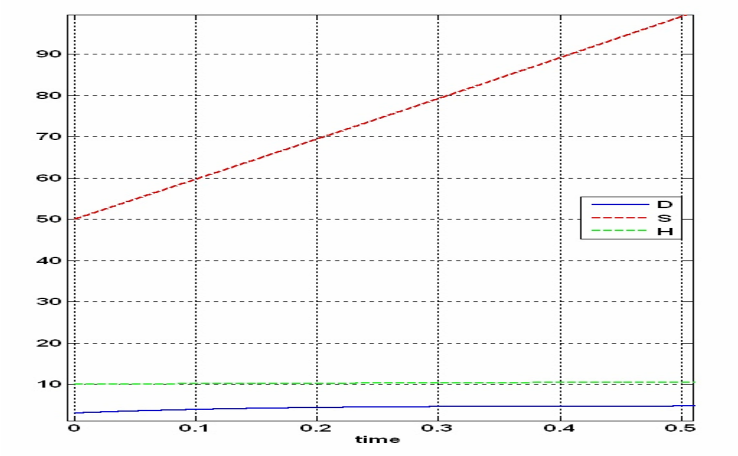

Figure 8. Highly stable society with growing synthesis, high emotional values attached to every concept, while knowledge accumulation stops; parameter values: D(t=0)= 3, H_0 = 10, S(t=0) = 50, S_0 = 1, S_1 = 10, a = 10, b = 1, d = 10, e=1.

Cultural historians might find examples of stagnating internally stable societies. Candidates are Ancient Egypt and contemporary Arab Moslem societies. Of course, these are only suggestions for future studies. Levels of differentiation, synthesis, and hierarchy can be measured by scientific means, and these data should be compared to the model. This would lead to model improvement, as well as to developing more detailed micro-neurodynamic models, simulating large societies of interacting agents, involving the mind subsystems of cognition and language [[xliii]]. And we hope that understanding of the processes of cultural stagnation will lead to overcoming these predicaments and to improvement of human condition.

8.5 Interacting cultures

Let us now study the interaction of cultures having different levels of differentiation and synthesis. Both are populations of agents characterized by NMF-minds and evolutionary eqs. (22, 23, 24). Culture k=1 is characterized by parameters leading to oscillating, potentially fast growing differentiation and a medium oscillating level of synthesis ("dynamic" culture). Culture

k=2 is characterized by slow growing, or stagnating differentiation, and high synthesis ("traditional" culture). In addition, there is a slow exchange by differentiation and synthesis among these two cultures (examples: the US and Mexico (or in general, immigrants to the US from more traditional societies); or academic-media culture within the US and "the rest" of the population). Evolutionary equations modified to account for the inflow and outflow of differentiation and synthesis can be written as

$$dD_k/dt = a_k\, D_k\, G(S_k) \;\; + x_k D_{\underline{k}} \tag{25}$$
$$dS_k/dt = -b_k D_k + d_k H_k + y_k S_{\underline{k}} \tag{26}$$
$$H_k \quad = H_{0k} + e_k{*}t \tag{27}$$

Here, the index $\underline{k}$ denotes the opposite culture, i.e., for k=1, $\underline{k}$ = 2, and v.v; parameters x_k and y_k determine the interaction or coupling between the two cultures. Fig. 9 illustrates sample solutions to these equations.

In Fig. 9 the evolution starts with two interacting cultures, one traditional and another dynamic. Due to the exchange of differentiation and synthesis among the cultures, traditional culture acquires differentiation, looses much of its synthesis, and becomes a dynamic culture. Let us emphasize that although we tried to find parameter values leading to less oscillations in differentiation and more stability, we did not find such solutions. Although parameters determining the exchange of differentiation and synthesis are symmetrical in two directions among cultures, it is interesting to note that traditional culture does not "stabilize" the dynamic one, the effect is mainly one-directional, that is, traditional culture acquires differentiated knowledge and dynamics. Wild swings of differentiation and synthesis subside a bit only after t > 5, when both cultures acquire a similar level of differentiated knowledge; then oscillations can partly counterweigh and stabilize each other at relatively high level of differentiation. It would be up to cultural historians and social psychologists, to judge if the beginning of this plot represents contemporary influence of American culture on the traditional societies. And if this figure explains why the influence of differentiation-knowledge and not highly-emotional stability-synthesis dominates cultural exchanges (unless "emotional-traditionalists" physically eliminate "knowledge-acquiring ones" during one of their period of weakness). Does partial stabilization beyond t > 5 represent the effect of multiculturalism and explain the vigor of contemporary American society?

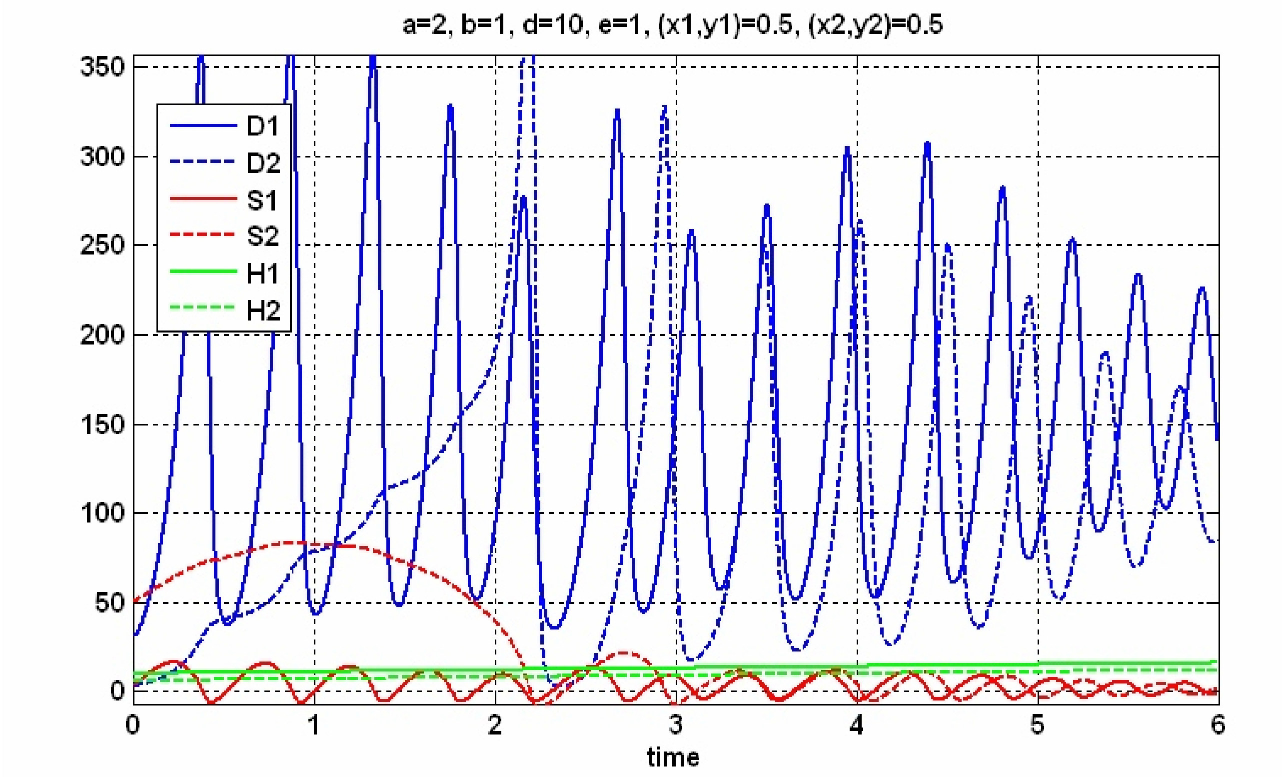

Figure 9. Effects of cultural exchange (k=1, solid lines: D(t=0)= 30, H_0 = 12, S(t=0) = 2, S_0 = 1, S_1 = 10, a = 2, b = 1, d = 10, e=1, x = 0.5, y = 0.5; k=2, dotted lines: D(t=0)= 3, H_0 = 10, S(t=0) = 50, S_0 = 1, S_1 = 10, a = 2, b = 1, d = 10, e=1, x = 0.5, y = 0.5). Transfer of differentiated knowledge to less-differentiated culture dominates exchange during t < 2 (dashed curve). In long run (t > 6) cultures stabilize each other and swings of differentiation and synthesis subside (note however, that in this example hierarchies were maintained at different levels; exchange of hierarchical structure would lead to the two cultures becoming identical).

This question is addressed in Fig. 10, which extends Fig. 9 to longer time scale. In long run (t > 5) cultures stabilize each other and swings of differentiation and synthesis subside. Note, that in this example hierarchies were maintained at different levels. Is this representative of Catholic and Protestant communities coexisting with approximately equal levels of differentiation and synthesis, but different hierarchies? This is a question for social psychologists. We would like to emphasize that co-existence of different cultures is beneficial in long run: both communities evolve with more stability.

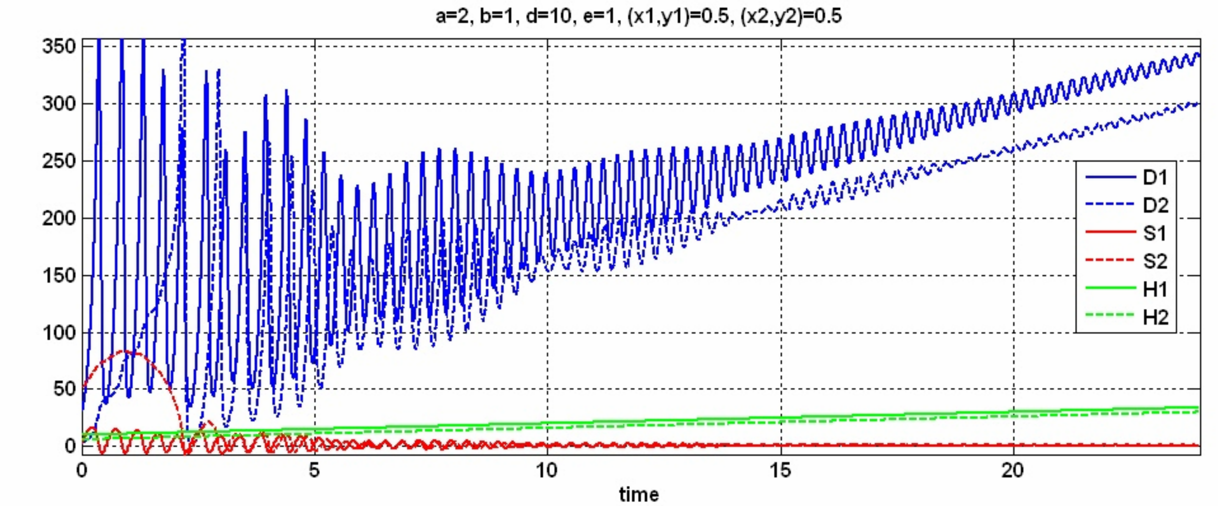

Figure 10. Effects of cultural exchange, same as Fig. 5 at longer time scale. In long run (t > 5) cultures stabilize each other and swings of differentiation and synthesis subside. Note, that in this example hierarchies were maintained at different levels (exchange of hierarchical structures would lead to the two cultures becoming identical).

9. Future Directions

9.1 Neurodynamics of music: synthesis of differentiated psyche

High levels of differentiation, according to models in the previous section, are not stable. By destroying synthesis, differentiation undermines the very basis for knowledge accumulation. This led in the previous section to wild oscillations in differentiation and synthesis. Here we analyze an important mechanism of preserving synthesis along with high level of differentiation, which will have to be accounted for in future models.

Let us repeat that synthesis, which is a feeling of meaning and purpose, is a necessary condition of human existence. Synthesis is threatened by the differentiation of knowledge. It is difficult to maintain synthesis in societies, like contemporary Western societies, which possess high differentiation and much abstract knowledge. In contrast, it is easier to maintain synthesis in traditional societies, where much of knowledge is directly related to the immediate needs of life. Since time immemorial, art and religion have connected conceptual knowledge with emotions and values, and these provided cultural means for maintaining synthesis along with differentiation. A particularly important role in this process belongs to music, since music directly appeals to emotions [[xliv],[xlv]].

Music appeared from the sounds of voice, i.e., from singing. The prosody or melody of voice sounds, rhythm, accent, tone, and pitch are governed by neural mechanisms in the brain. Images of neural activity (obtained by magnetic resonance imaging, MRI) show that the human brain has *two centers controlling melody of speech*; an ancient center located in the limbic system, and a recent one in the cerebral cortex. The ancient center is connected with direct uncontrollable emotions, whereas the recent center is connected with concepts and consciously controlled emotions. This fact was learned from medical cases in which patients with a damaged cortex lost the ability for speaking and understanding complex phrases, while still were able to

comprehend sharply emotional speech [xlvi].

Prosody of speech in primates is governed by a single ancient emotional center in the limbic system. Conceptual and emotional systems in animals are less differentiated than in humans. Sounds of animal cries engage the entire psyche, rather than concepts and emotions separately. An ape or bird seeing danger does not think about what to say to its fellows. A cry of danger is *inseparably* fused with recognition of a dangerous situation, and with a command to oneself and to the entire flock: "Fly!" An evaluation (emotion of fear), understanding (concept of danger), and behavior (cry and wing sweep) – are not differentiated. The conscious and unconscious are not separated: recognizing danger, crying, and flying away is a fused concept-emotion-behavioral *synthetic* form of thought-action. Birds and apes can not control their larynx muscles *voluntarily*.

Emotions-evaluations in humans have separated from concepts-representations and from behavior. For example, when sitting around the table and discussing snakes, we do not jump on the table uncontrollably in fear every time "snakes" are mentioned. This *differentiation* of concepts and emotions is driven by language. Prosody or melody of speech is related to cognition and emotions through aesthetic emotions. This connection of concepts with emotions, conscious models with unconscious archetypes, is *synthesis*. *The human voice engages concepts and emotions. Melody of voice is perceived by ancient neural centers involved with archetypes, whereas conceptual contents of language involves conscious concepts. Human voice, therefore, involves both concepts and emotions; its melody is perceived by both conscious and unconscious; it maintains synthesis and creates wholeness in psyche.* [xlvii]

Over thousands of years of cultural evolution, music perfected this inborn ability. *Musical sound engages the human being as a whole*—such is the nature of archetypes, ancient, vague, undifferentiated emotions-concepts of the mind. Archetypes are non-differentiated, their emotional and conceptual contents, their high and low are fused and exist only as possibilities. By turning to archetypes, music gets to the most ancient unconscious depths as well as to the loftiest ideas of the meaning of existence. This is why folk songs, popular songs, or opera airs might affect a person more strongly than words or music separately. The synthetic impact of a song, connecting the conscious and unconscious, explains the fact that sometimes mediocre lyrics combined with second-rate music might still impact listeners. When music and poetry truly correspond with each other and reach high artistic levels, a powerful psychological effect occurs. This effect uncovers mechanisms of the mysterious co-belonging of music and poetry. *High forms* of art effect synthesis of the most important models touching the meaning of human existence. *Popular songs*, through interaction of words and sounds, connect the usual words of everyday life with the depths of the unconscious. This explains why in contemporary culture, with its tremendous number of differentiated concepts and lack of meaning, such an important role is taken by popular songs. [ix,xxxiv,xlviii].

Whereas language evolved as the main mechanism for the differentiation of concepts, music evolved as the main mechanism for the differentiation of emotions (conscious emotions in the cortex). This differentiation of emotions is necessary for unifying differentiated consciousness: synthesis of differentiated knowledge entails emotional interactions among concepts [xlix]. This mechanism may remedy a disturbing aspect of the oscillating solutions considered in the previous section, i.e., the wild oscillations of differentiation and synthesis. During every period of cultural slowdown about 85% of knowledge collapsed. In previous sections we defined the knowledge instinct as the maximization of similarity, and we defined aesthetic emotions as changes in similarity. Future research will have to make the next step,

which will define the mechanism by which differentiated aesthetic emotions unify contradictory aspects of knowledge. We will model neural processes, in which diverse emotions created by music unify contradictory concepts in their manifold relations to our cognition as a whole. We will have to understand processes in which the knowledge instinct differentiates itself and the synthesis of differentiated knowledge is achieved.

9.2 Experimental evidence

The knowledge instinct is clearly a part of mind operations [i,ii,iii]. Can we prove its ubiquitous nature and connection to emotional satisfaction or dissatisfaction? Can we measure aesthetic emotions during perception (when it is usually subliminal)? Can we measure aesthetic emotions during more complex cognition (when it is more conscious)? Does brain compute similarity measures, and if so, how is it done? Does it relate to aesthetic emotions as predicted by the knowledge instinct theory? Does it operate in a similar way at higher levels in the hierarchy of the mind? Operations of the differentiated knowledge instinct, and the emotional influence of concepts on cognition of other concepts, are virtually obvious experimental facts. However, detailed quantitative studies of this phenomenon are missing. For example, can we prove that emotionally sophisticated people can better tolerate cognitive dissonances (that is, conceptual contradictions) than people less sophisticated emotionally (it would be important to control other variables, say IQ).

Dan Levine studies emotional effects on learning [l]. In his experiments normal subjects gradually accumulated cognitive knowledge, whereas emotionally impaired patients could not properly accumulate cognitive knowledge. Subject emotions in his experiments were not related to any bodily need, rather these were aesthetic emotions. Are these aesthetic emotions limited to the cortex, or are ancient emotional mechanisms also involved?

Mechanisms of conceptual differentiation at a single level in a hierarchy described in section 4 correspond to psychological and neurophysiological experimental evidence. These include the interaction between bottom-up and top-down signals, and resonant matching between them as a foundation for perception [vi,li]. Experimental evidence is less certain for these mechanisms being repeated at each hierarchical level. Experimental evidence for dynamic logic is limited to the fact that imagination (concept-models voluntary recollected from memory with closed eyes) are vague and fuzzy relative to actual perceptions with open eyes. Dynamic logic makes a specific suggestion that top-down (model) signals form a vague-fuzzy image that gradually becomes more specific until it matches the perceived object. This prediction might be amenable to direct verification in psychological experiments.

Norman Weinberger studied the detection of a specific acoustic tone, using an electrode to measure the response from the cellular receptive fields for acoustic frequencies in the brain [lii]. Dynamic logic predicts that the initial response will be fuzzy and vague. During learning, the neural response will gradually become more specific, more “tuned.” This trend was actually experimentally observed. As expected according to dynamic logic, the frequency receptive field became more “tuned,” in the auditory cortex. The auditory thalamus, however, an evolutionarily older brain region, did not exhibit dynamic-logic learning. It would be more difficult to confirm or disprove this mechanism at higher levels in the hierarchy.

9.3 Problems for future research

Future experimental research will need to examine, in detail, the nature of hierarchical interactions, including the mechanisms of learning hierarchy. This research may reveal to what extent the hierarchy is inborn vs. adaptively learned. Studies of the neurodynamics of interacting language and cognition have already begun [x,xii,liii]. Future research will need to model the differentiated nature of the knowledge instinct. Unsolved problems include: neural mechanisms of emerging hierarchy, interactions between cognitive hierarchy and language hierarchy [xi,xii]; differentiated forms of the knowledge instinct accounting for emotional interactions among concepts in processes of cognition, the infinite variety of aesthetic emotions perceived in music, their relationships to mechanisms of synthesis [xxxiv,xlvii,xlviii]; neural mechanisms of interactions of differentiation and synthesis, and evolution of these mechanisms in the development of the mind during cultural evolution.

Cultural historians can use the results of this chapter as a tool for understanding the psychological mechanisms of cultural evolution. The results may explain how differentiation and synthesis have interacted with language, religion, art, and especially music, and how these interactions have shaped the evolution of various cultures. Social psychologists can use the results of this chapter as a tool for understanding the psychological mechanisms governing present conditions. It is possible to measure the levels of differentiation and synthesis in various societies, and to use this knowledge for improving human conditions around the world. It will also be possible to predict future cultural developments, and to use this knowledge for preventing strife and stagnation, and for stimulating wellbeing.

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Acronyms:

BCE	Before the Common Era
CC	Combinatorial Complexity
DL	Dynamic Logic
NMF	Neural Modeling Fields